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Stock Price Prediction Using Optimal Network Based Twitter Sentiment Analysis

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Abstract: In recent times, stock price prediction helps to determine the future stock prices of any financial exchange. Accurate forecasting of stock prices can result in huge profits to the investors. The prediction of stock market is a tedious process which involves different factors such as politics, economic growth, interest rate, etc. The recent development of social networking sites enables the investors to discuss the stock market details such as profit, future stock prices, etc. The proper identification of sentiments posted by the investors in social media can be utilized for predicting the upcoming stock prices. With this motivation, this paper focuses on the design of effective stock price prediction using dragonfly algorithm (DFA) based deep belief network (DBN) model. The DFA-DBN technique aims to properly determine the sentiments of the investors from Twitter data and forecast future stock prices. From Twitter data, the DFA-DBN technique attempts to accurately determine the sentiments of investors, as well as predict future stock prices. For accurate stock price prediction, the proposed DFA-DBN model includes the development of a DBN model. The proposed DFA-DBN model involves the design of DBN model for accurate prediction of stock prices. Besides, the hyperparameter tuning of the DBN technique is performed by utilize of DFA and thereby boosts the overall prediction performance. For validating the supremacy of the DFA-DBN model, a comprehensive experimental analysis takes place and the results demonstrate the accurate prediction of stock prices. A predicted DFA-DBN algorithm with a higher accuracy of 94.97 percent is available. On the basis of the data in the tables and figures above, the DFA-DBN approach has been demonstrated to be an effective instrument for anticipating stock price fluctuations.

Keywords: Stock price prediction; Twitter; sentiment analysis; deep learning; hyperparameter optimization

1 Introduction

The popularity of microblogging could be described by their distinctive features like accessibility and convenience that enables user to instantaneously disseminate and respond data with no restrictions/with limited on content. Currently, Twitter is the 10th most widespread website around the world with 300 million active users once-a-month. Microblogging is a social media platform that blends short messaging with the creation of content. A microblog can be used to transmit short messages to an online audience in order to enhance interaction. Twitter, Instagram, Facebook, and Pinterest are all popular social media platforms for microblogging. Certain microblogging systems allow users to restrict who has access to their microblogs or to publish entries in ways other than the web-based interface. Texting, instant messaging, e-mail, digital audio, and digital video are all examples of these technologies. Twitter. In the world of microblogging, Twitter is the most well-known platform. The following image is a representation of the popularity of microblogging as a result of its distinguishing characteristics. Microblogging sites are popular because they provide content in formats that are appealing to today's users. While there are several microblogging platforms available, we've determined that Twitter, Pinterest, Tumblr, Instagram, and Facebook are the frontrunners. Additionally, Reddit and LinkedIn are catching up quickly. Twitter has been upgrading hundreds of millions of times a day with contents differing to an individual everyday life update to global events and news [1]. Twitter enables user to make own profiles that other might 'follow' or subscribe to, post status update called as 'tweets' restricted to 140 characters and for interacting with other people using 'replies'. Initially, Twitter was setup as a kind of transmission platform designed to permit friends for keeping tabs on each other. A stock API is a programming interface that allows a source to get a stream of real-time stock market data. Many existing brokerage platforms, for example, rely on a stock API to offer real-time data to its investors in order to make buying and selling choices Because of the accessibility of an application programming interface (API), that stores tweet posts which might be accessed by the researcher, and their convenient features like filtering via variables such as keywords and location [2], Twitter has stimulated researchers to be interested and explores their potential away from that of social media [3]. While calculating the structural property of Twitter as social network study has concentrated on users effectively.

Content analysis study has concentrated on exploring the motivation, content, and virality of twitters. Deepak Kumar et al. [4] classified the motivation of twitters into; daily chatter, conversations, reporting news, and sharing information. Sentimental analysis study has concentrated on using Twitter chatter sentiments to predict the behaviors. Satpathy et al. [5] arguing that even though all the tweets represent individual opinions, an aggregate sample must give precise representations of public sentiment. Though it is accepted generally that stock market price depends to a large extent on novel data and follows a random pattern, lot of research has attempted for predicting the stock market behaviors with external stimuli based on behavioral economics which emphasizes the significant part of the sentiment in making decisions.

Stock market predictions aim is to decide the future movement of the stock values of a financial transaction. The precise predictions of stake price movements would lead to additional profit investors could generate [6]. Forecasting how the stock markets would move is the most difficult problem because of the several aspects included in the stock predictions, like economic growth interest, rates, and politics make the stock market very hard and volatile for the accurate prediction [7]. The prediction of share provides high possibility for the profits and is the main objective for studies in this field; knowledge of stock movement within a second might leads to higher profit [8]. As stock investments are a main financial market event, a lack of detailed information and precise knowledge will lead to an unavoidable loss of investments. The stock market prediction is a tedious process since market movement is often subjected to uncertainties [9]. The stock market predictive method is separated into 2 major classes: fundamental and technical analysis. Technical analysis focus on exploring past stock price for predicting future stock value (viz., its focus on the direction of price). At the same time, fundamental analysis are based mainly on exploring unstructured textual data such as earning reports and financial news. Several authors believe that technical analysis approach could forecast the stock market movement [10].

Motivated by the intrinsic relationship between the sentiments and stock prices, this study designs a new stock price prediction using dragonfly algorithm (DFA) based deep belief network (DBN) model. The proposed DFA-DBN technique comprises preprocessing prediction and hyperparameter tuning. Moreover, the DBN technique has been implemented for predicting the upcoming stock prices by analyzing the sentiments in Twitter data. Furthermore, the hyperparameter optimizer using DFA is derived to optimally choose the hyperparameters involves in it. A comprehensive simulation analysis is carried out on Twitter data and the results are inspected under varying aspects.

2 Related Work

Generally, Zach [11] proposes that has been restricted proof of direct links among market performance and political events because of its complexity in measuring political alteration. In addition to this, Klibanoff et al. [12] conjecture that the issue with this thread of researches is that generally surveys are retrospective and, thus, determinant of investor behaviors like investment sentiments are no longer observable.

Most recent surveys appear to confirm the presence of relationships among stock market movements and political events and news. The stock market returns (Israeli) are further extreme follows political events, when [13] finding that there is an important relationship among financial crises and political uncertainty afterward controlling their analysis for the aspects like market contagion and difference in economic condition of the sampled nation. Lastly, the relationships among trust in the government and public sentiment are very important for the stock market investor when compared to non-participant, recommending that public moods regarding politics are a factor in making investment decisions [14].

Vinothini et al. [15] construct LSTM based DL networks to forecast the closing prices of the stock and relate the predictive accuracy of the ML model using the LSTM models. Further, we increase the prediction models by incorporating a sentimental analysis model on twitters information for correlating the public sentiments of stock price with the market sentiments. It is made by the twitter sentiments and earlier week closing value for predicting stock price movements for the following weeks.

Jin et al. [16] proposed a DL based stock market predictive method which considers investor sentimental tendency. Initially, proposed to include investor sentiments for predicting stocks that could efficiently enhance the predictive performance. They proposed to decompose gradually the complicated series of stock prices by adapting EMD method that yields improved predictive performance. Next, adapt LSTM model because of its advantage of exploring relationship between time series data via its memory function. In Guo et al. [17], a new social network sentimental analysis method has been presented according to the TSS for realtime predictions of the future stock market price FTSE 100, related to traditional econometric model of investor sentiments based CEFD method. The presented TSS method feature a novel baseline relation method that exhibits better predictive performance, as well as reduces the computational burden, and allows faster decision making without the knowledge of past information. Classification modelling, Polynomial regression, and lexicon based sentimental analysis were conducted.

Gupta et al. [18] explore the Stock Twits content and extract financial sentiments with a collection of text featurization and ML techniques. The correlations among the aggregated everyday sentiments and stock price movements were studied later. Lastly, the sentimental data is utilized as well as the historical stock time series data to enhance the performance of stock price movement predictions. Mohan et al. [19] improved the performance of stock price prediction by collecting a huge number of time series data and analyze it regarding related news articles, with DL methods. The gathered datasets include everyday stock prices for S&P500 Company to 5 years and over 265,000 financial news articles associated with this company.

3 The Proposed Stock Price Prediction Model

In order to accomplish effective stock price prediction using Twitter data, this study has designed a new DFA-DBN model and it operates on three major stages. At the initial stage, the Twitter data is preprocessed to get rid of unwanted data and transform it into a meaningful format. Next, in the second stage, the predictive process using DBN model is carried out. Finally, the parameter tuning of the DBN technique is performed by utilize of DFA and it results in improved prediction results. Fig. 1 demonstrates the overall process of proposed DFA-DBN model.

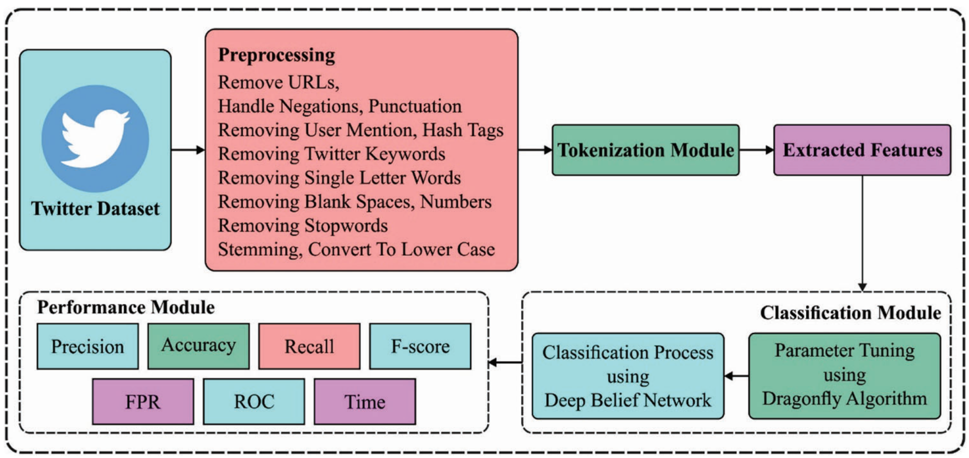

Figure 1: Overall process of DFA-DBN model

3.1 Stage 1: Data Preprocessing

In the preprocessing step, distinct twitter data sets are developed for manipulation. This type of tweet contains several numbers, HTML tags, punctuation, multiple spaces, and single characters. Some functions have been utilized for cleaning datasets in these steps. The symbol '⟨⟩' has been replaced by an empty space. Again, all characters that don't specify any useful transmission has been replaced by a space correspondingly. Lastly, all multiple spaces have been detached from this tweet. Afterward the preprocessing step, tokenization procedure is utilized for generating a word to index dictionary where every single word is generated as a key in the corpus. Using word embedded was helpful for extracting important words and explore semantic and similarity relations accurately. Lastly, an embedding matrix is produced where every single row number matches with index of words in the corpus. The raw tweet contains text instances that could not deal with ML process. Thus, run tokenization and data preprocessing procedure for making it implementable for classification and clustering computations.

3.2 Stage 2: Prediction Process

The next stage of preprocessing is the prediction process which can be performed by the use of DBN model. DBN is a class of deep generative method which made up of l stack of RBM. The primary objective of DBN is the weight initiation of a DNN method for producing optimal methods compared to the models through an arbitrary weight. This method makes the prediction very efficient. On the other hand, DBN could be efficiently utilized for performing layer-wise pre-training proposed to initiate training of a BP model. The energy based probabilistic method is a general model utilized for making a joint distribution among observed data, x. and hidden variable, h, according to the following formula:

$$P\left(v,\ h^{1},\ \ldots,\ h^{m}\right)=\left(\prod_{i=1}^{m-2}P\left(h^{i}|h^{i+1}\right)\right).P\left(h^{m-1}|h^{m}\right), \tag{1}$$

whereas $\mathrm{l}=\mathrm{h}^{\mathrm{o}}$, $\mathrm{P}(\mathrm{h}^{\mathrm{i}}|\mathrm{h}^{\mathrm{i}+1})$ represent the conditional distribution for hidden to hidden units in RBM associated with the k^{th} level of DBN, and $\mathrm{P}(\mathrm{h}^{\mathrm{m}-1}|\mathrm{h}^{\mathrm{m}})$ denotes the hidden-wise joint distribution in highest level RBM. In every layer, estimated output has been employed as an input for the following layers [20]. Fig. 2 portrays the framework of DBN technique.

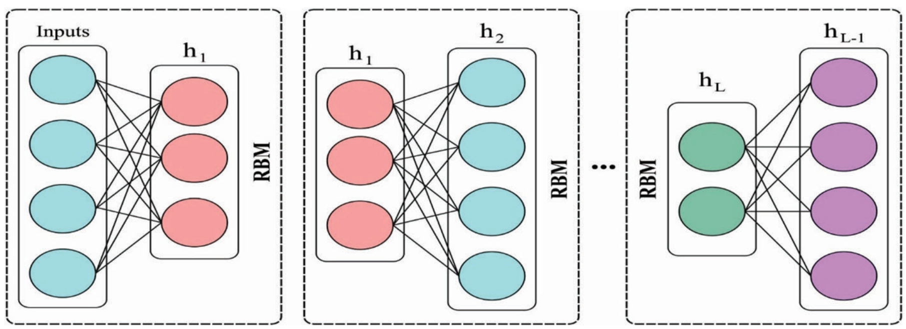

Figure 2: DBN structure

RBM is a type of Boltzmann machine without internal layer connections in the hidden and visible layers. During this method, the likelihood of joint configuration (l,h) is determined by:

$$\Pr(\mathrm{l},\ \mathrm{h})=\frac{\exp(-\mathrm{Energy}(\mathrm{l},\mathrm{h}))}{\mathrm{Z}}, \tag{2}$$

In which $\mathrm{Z}=\sum_{\mathrm{i,j}}\exp\left(-\mathrm{Energy}\left(\mathrm{l_i},\ \mathrm{h_j}\right)\right)$ is known as regularization factor. The likelihood of visible units is attained using the summation of each hidden unit.

$$\mathrm{P}(\nu)=\frac{1}{\mathrm{Z}}\sum_{\mathrm{h}}\exp(\mathrm{Energy}(\mathrm{l},\ \mathrm{h})) \tag{3}$$

The derivation of the logarithm of likelihood formula abovementioned is determined by:

$$\frac{\partial\log(\mathrm{P}(\nu))}{\partial\theta}=\frac{\partial\sum_{\mathrm{h}}\exp(-\mathrm{Energy}(\mathrm{l},\mathrm{h}))}{\partial\theta}-\frac{\partial\log(\mathrm{Z})}{\partial\theta}=\phi^{+}-\phi^{-}, \tag{4}$$

Let ϕ^{+} & ϕ^{-} represents negative and positive stages, correspondingly. Estimate the positive phases are simple due to the absence of internal connections among hidden/visible units. The conditional likelihood for other pairs of hidden units is attained using:

$$\mathrm{P}\left(\mathrm{h_j}=1|\mathrm{l}\right)=\frac{\mathrm{e}^{\mathrm{c_j}+\mathrm{W_j}\mathrm{l}}}{1+\mathrm{e}^{\mathrm{c_j}+\mathrm{W_j}\mathrm{l}}}=\mathrm{sigm}\left(\mathrm{c_j}+\sum\ \mathrm{W_j}\mathrm{l}\right), \tag{5}$$

In which $\mathrm{W_j}$ represent jth row of W and sigm(x) denotes the sigmoid functions. Next, in the negative stage, must be estimated for each hidden and visible unit. Most of the presented algorithms for approximating log-probability gradient is CD. Assume hidden unit as binary, each visible variable is divided as to few classes according to the batch size determined in the initial step. Next, the hidden unit is estimated by Eq. (6).

$$P(h_j) = \mathrm{sigm}\left(c_j + \sum_i w_{i,j} l_i\right) \tag{6}$$

Lastly, the hidden units will turn on when the likelihood is higher when compared to the threshold. In order to update visible unit, it is widely used likelihood, p_i, i.e., calculated by:

$$P(\nu_i) = b_i + \sum_j w_{i,j} h_j \tag{7}$$

Afterward evaluating the gradient, it is potential to upgrade parameters, bias, and weight. The 2 major variables, momentum learning and rate, could enhance the upgraded parameter based on the prior one. Learning rate is multiplied with ΔW. When this variable is larger, the recreation error will be increased, and when it is lower, the processing time would be larger. It can be utilized afterward calculating batch data and update parameter, therefore, multiplied with W_{old}.

3.3 Stage 3: Hyperparameter Tuning Process

At the final stage, the hyperparameter optimizer using DFA is derived which helps to optimally select the hyperparameters involved in the DBN model. The DFA is dependent upon the swarming performance of dragonflies, which follow 3 fundamental principles:

Separation: Static collision avoidance of individual dragonflies in neighborhoods.

Alignment: The velocity corresponding of individual dragonflies in neighborhoods.

Cohesion: The tendency of individual dragonflies towards neighborhood centers of a mass.

In addition, any swarm of living creatures could follows its survival instinct. Therefore, each dragonfly individual also needs to be attracted towards food source (food attraction) and distract outwards predator (predator distraction). In conclusion, the swarm behaviors of the dragonfly community could be described with these 5 major aspects.

To simulate the swarm behaviors of the dragonfly, the above-mentioned features have to be arithmetically modeled in the following. The separation motion is formulated by:

$$S_{(i,t)} = -\sum_{j=1}^{N} X_{(i,t)} - X_{(i,t)} \tag{8}$$

where $S_{(i,t)} =$ separation motion for i^{th} individual dragonfly at tth iteration; $X_{(j,t)} =$ location of the jth neighboring individual dragonfly at tth iteration [21]; $N =$ numbers of neighboring dragonfly individual; and $X_{(i,t)} =$ location of the i^{th} individual dragonfly at tth iteration.

The alignment motion is estimated as:

$$A_{(i,t)} = \frac{\sum_{j=1}^{N} V_{(j,t)}}{N} \tag{9}$$

Let $A_{(i,t)} =$ alignment motion to ith individual dragonfly at tth iteration; and $hV_{(j,t)} =$ velocity of jth neighboring individual dragonfly at tth iteration.

The cohesion motion is quantified as:

$$c_{(i,t)} = \frac{\sum_{j=1}^{N} X_{(j,t)}}{N} - X_{(i,t)} \tag{10}$$

where $C_{(i,t)} =$ cohesion motion to i^{th} individual dragonflies at nh iteration. The food attraction motions are evaluated as:

$$F_{(i,t)} = X_{(food,t)} - C_{(i,t)} \tag{11}$$

Let $X_{(food,t)} =$ location of the food source at tth iteration; and $F_{(i,t)} =$ food attraction motion for ith individual dragonfly at nh iteration. The food is taken into account as individual dragonflies with optimal objective function found until now. The predator distraction can be measured as:

$$E_{(i,t)} = X_{(enemy,t)} + X_{(i,t)} \tag{12}$$

where $X_{(enemy,t)} =$ location of the predator at nh iterations; and $E_{(i,t)} =$ predator distraction motion for ith individual dragonfly at nh iteration. The predators are taken into account as individual dragonflies with worst objective function found until now.

The integration of above-mentioned motion could forecast the corrective patterns of the individual dragonfly in all iterations. The position of individual dragonfly is upgraded in all iterations with the present location of an individual dragonfly $\left[X_{(i,t)}\right]$ as well as step vectors $\left[\Delta X_{(i,t)}\right]$. Indeed, the presented step vectors are similar to the velocity vectors in the PSO model, also the process of upgrading the position of individual dragonflies in DA depends on the architecture of PSO model. The step vectors demonstrate the motion direction per individual dragonfly, can be determined by:

$$\Delta X_{(i,t+1)} = \left(s \times S_{(i,t)} + a \times A_{(i,t)} + c \times C_{(i,t)} + f \times F_{(i,t)} + e \times E_{(i,t)}\right) + w \times \Delta X_{(i,t)} \tag{13}$$

Let $a =$ alignment weight; $s =$ separation weight; $f =$ food attraction weight; $c =$ cohesion weight; $w =$ inertia weight and $e =$ predator distraction weight. After evaluating the step vector, the upgraded location vector can be measured as

$$X_{(i,t+1)} = X_{(i,t)} + \Delta X_{(i,t)} \tag{14}$$

By interfering with the predator weight, separation, alignment, cohesion, and food attraction $(w, s,\ a,\ c,\ f, \text{and } e)$, distinct intensification and diversification behaviors could be attained using the optimization.

4 Experimental Validation

In this section, the performance validation of the DFA-DBN technique takes place on Twitter dataset. The results are examined in-terms of training, validation, and testing dataset. Tab. 1 gives comprehensive outcomes analysis of the DFA-DBN technique under different measures. Fig. 3 portrays the results analysis of the DFA-DBN technique on the applied training dataset. The results reported that the DFA-DBN manner has accomplished effectual results with a precision of 0.9536, sensitivity of 0.9084, specificity of 0.9748, accuracy of 0.9506, F-score of 0.9304, MCC of 0.8928, and FPR of 0.0252.

Table 1: Result analysis of DFA-DBN model

Measures	Training set	Validation set	Testing set
Precision	0.9536	0.9526	0.9521
Sensitivity	0.9084	0.9069	0.9060
Specificity	0.9748	0.9742	0.9739
Accuracy	0.9506	0.9497	0.9492
F-Score	0.9304	0.9292	0.9285
Mathews Correlation Coefficient	0.8928	0.8909	0.8898
False Positive Rate	0.0252	0.0258	0.0261

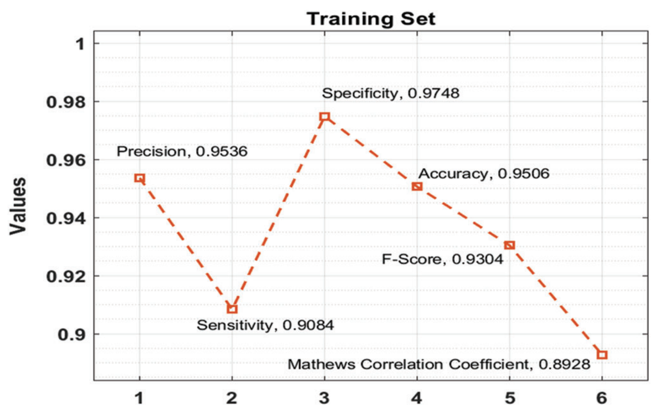

Figure 3: Training set analysis of DFA-DBN model with different measures

Fig. 4 depicts the outcomes analysis of the DFA-DBN methodology on the applied validation dataset. The outcomes portrayed that the DFA-DBN methodology has accomplished efficient results with the precision of 0.9526, sensitivity of 0.9069, specificity of 0.9742, accuracy of 0.9497, F-score of 0.9292, MCC of 0.8909, and FPR of 0.0258.

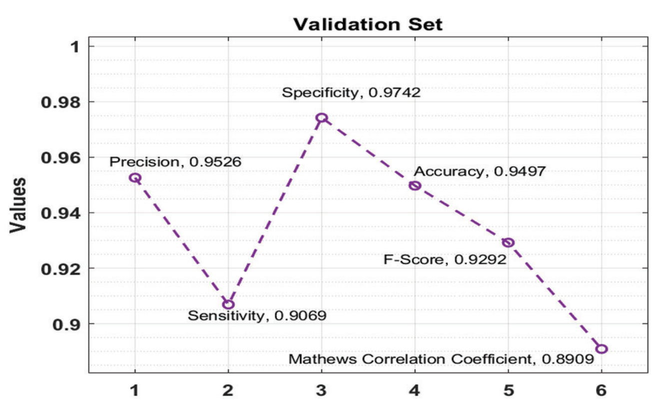

Figure 4: Validation set analysis of DFA-DBN model with different measures

Fig. 5 exhibits the outcomes analysis of the DFA-DBN approach on the applied testing dataset. The outperforms stated that the DFA-DBN algorithm has able effective results with the precision of 0.9521, sensitivity of 0.9060, specificity of 0.9739, accuracy of 0.9492, F-score of 0.9285, MCC of 0.8898, and FPR of 0.0261.

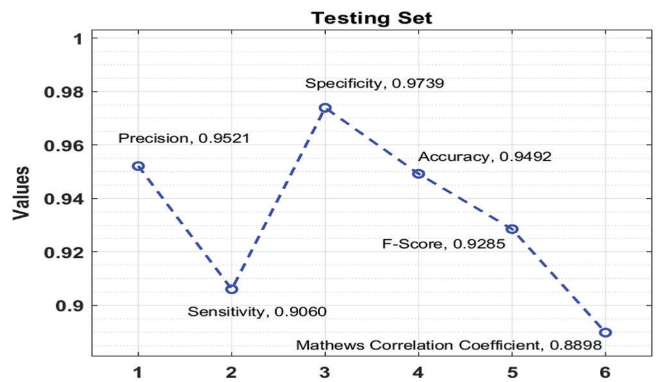

Figure 5: Testing set analysis of DFA-DBN model with different measures

Next, Fig. 6 demonstrates the ROC analysis of the DFA-DBN manner on the applied training, testing, and validation datasets. The figure exhibited that the DFA-DBN technique has accomplished a higher ROC of 99.1091%, 98.1837%, and 98.9783% on the test training, testing, and validation datasets.

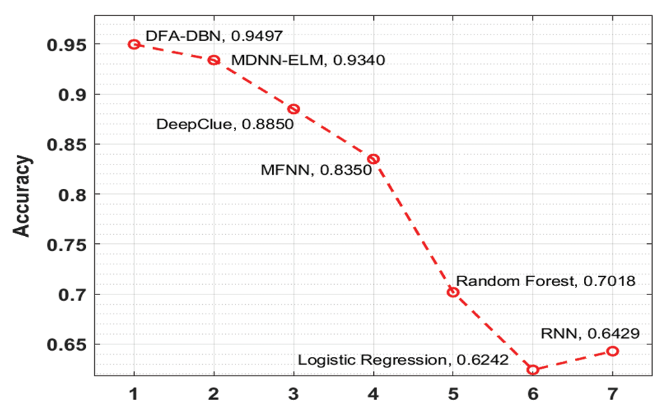

Figure 6: Accuracy analysis of DFA-DBN model with recent methods

Eventually, a detailed comparative outcomes analysis of the DFA-DBN manner with recent techniques takes place in Tab. 2 [22,23]. The outcomes make sure that the DFA-DBN approach has resulted in maximal performance related to another approach.

Fig. 6 scrutinizes the accuracy analysis of the DFA-DBN manner with recent approaches. The figure depicted that the RF, LR, and RNN approaches have accomplished to a lesser accuracy of 70.18%, 62.42%, and 64.29% correspondingly. Similarly, the DeepClue and MFNN systems have reached a moderate accuracy of 88.5% and 83.50% correspondingly. Followed by, the MDNN-ELM manner has resulted in a competitive accuracy of 93.40%, the projected DFA-DBN algorithm has exhibited higher with increased accuracy of 94.97%. From the aforementioned tables and figures, it could be stated that the DFA-DBN methodology is established that an appropriate tool to forecast stock prices.

Table 2: Comparative analysis of DFA-DBN model with existing techniques

Methods	Precision	Recall	F-score	Accuracy	FPR	Time
Proposed DFA-DBN	0.9536	0.9069	0.9292	0.9497	0.0258	11.07
MDNN-ELM	–	–	–	0.9340	6.60	19.90
DeepClue	–	–	–	0.8850	11.50	21.80
MFNN	–	–	–	0.8350	16.50	27.80
Random Forest	0.7110	0.7020	0.6900	0.7018	–	–
Logistic Regression	0.6210	0.6240	0.6210	0.6242	–	–
RNN	0.6345	0.6365	0.6246	0.6429	–	–

5 Conclusion

This study has presented a DFA-DBN technique to predict future stock prices using Twitter data. The proposed DFA-DBN technique involves preprocessing, DBN based prediction, and DFA based hyperparameter optimization. The application of DFA to properly adjust the hyperparameters involved in the DBN model helps to accomplish maximum prediction results. A comprehensive simulation analysis is carried out on Twitter data and the results are inspected under varying aspects. The resultant comparative analysis demonstrated that the DFA-DBN technique results in improved stock price predictive performance on the other approaches with respect to distinct measures. As a part of future scope, the presented DFA-DBN technique can be deployed in big data environment and validate on large scale real time datasets.

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